Probabilistic change mapping from airborne LiDAR for post-disaster damage assessment

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ARL — The University of Texas at Austin

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Introduction

Summary

Change detection using remote sensing has become increasingly important for characterization of natural disasters. Pre- and post-event LiDAR data can be used to identify and quantify changes. The main challenge consists of producing reliable change maps that are **robust** to differences in collection conditions, free of processing artifacts, and that take into account various sources of **uncertainty** such as different point densities, different acquisition geometries, georeferencing errors and geometric discrepancies.

We present a novel technique that accounts for these sources of uncertainty, and enables the creation of **statistically significant change detection maps**. The technique makes use of Bayesian inference to estimate uncertainty maps from LiDAR point clouds. Incorporation of uncertainties enables a change detection that is robust to noise due to ranging, position and attitude errors, as well as "roughness" in vegetation scans.

The validation of the method was done by use of small-scale models scanned with a terrestrial LiDAR in a laboratory setting. The method was then applied to two airborne collects of the Monterey Peninsula, California acquired in 2011 and 2012. The data have significantly different point densities (4 vs. 40 pts/m2) and some misregistration errors. A new **point cloud registration** technique was developed to correct systematic shifts due to GPS and INS errors. Sparse changes were detected and interpreted mostly as construction and natural landscape evolution.

Dataset description

WSI

- WSI for Naval Postgraduate School Monterey, CA
- Collection date: 2012/10-2012/11
- Scanner used: Optech ALTM Orion-C200
- Flight parameters: 450 m AGL, 100% overlap, 60% sidelap
- Scanning geometry: 66 kHz PRF, 30 deg FOV, sawtooth
- Point density: 40-80 pts/m2 average
- Posted accuracy: 7 cm vertical, 20 cm horizontal

NOAA

- Fugro EarthData, Inc. for the NOAA CA Coastal Conservancy Coastal Lidar Project
- Collection date: 2009/10-2011/08
- Scanner used: Leica ALS60 (oscillating mirror)
- Flight parameters: 1800 m AGL, >50% overlap
- Scanning geometry: 120 kHz PRF, sinusoidal
- Point density: 5-8 pts/m2 average
- Posted accuracy: 18 cm vertical, 50 cm horizontal

AMBAG *[not used due to quality concerns]*

- Digital Mapping Inc. for the Association of Monterey Bay Area Governments (AMBAG)
- Collection date: before 2010/08
- Scanner used: Optech ALTM Gemini (oscillating mirror)
- Flight parameters: 1200 m AGL, 50% overlap
- Scanning geometry: 100 kHz PRF, 40 Hz line scan, +-25 deg, sawtooth
- Point density: 2-4 pts/m2 average
- Posted accuracy: 23 cm vertical, 35 cm horizontal *[underestimated]*

Context:
Remote Sensing for Improved Earthquake Response

NPS-DHS Project Page   *Concept of tiered product delivery*

www.nps.edu/Academics/Centers/RSC/Projects/Earthquake-Response-Project.html

Change detection ingredients

- ➡ Bayesian Inference for parameter and error estimation
- ➡ Gridding: compare DSM generated from point clouds (indep.)
- ➡ Local polynomial surface model (linear in current implem.)
- ➡ Kernel regression to infer model parameters
- ➡ Empirical errors from local residuals
- ➡ Heavy-tailed Student-t distributions for low point densities
- ➡ Probabilistic comparison of local height distributions
- ➡ Approximations to allow fast comparisons
- ➡ Simple model to account for geometric errors
- ➡ Preset significance levels for change detection
- ➡ Intuitive visualization method

Automatic dataset registration

- ➡ Bayesian Inference for 3D shift estimation
- ➡ Simultaneous gridding of both datasets into the same DSM
- ➡ Approximation 1 - Dirac marginalization
- ➡ Approximation 2 - Density-weighted log variances
- ➡ Approximation 3 - Piecewise constant shift
- ➡ Nonlinear Conjugate Gradient optimization


NONPARAMETRIC KERNEL REGRESSION
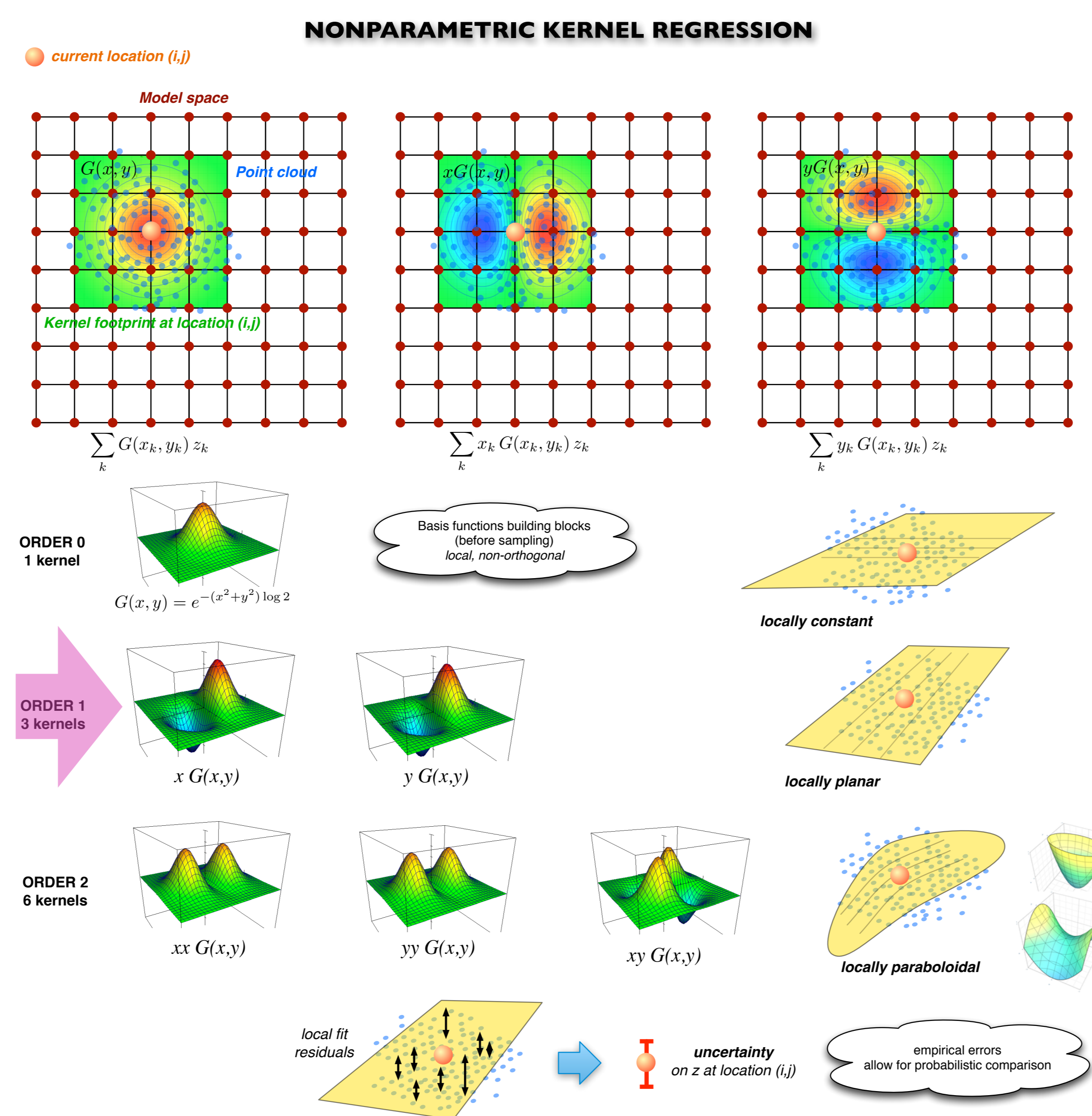
Principles of nonparametric kernel regression method. For each grid location a 4x4 grid cell patch is considered (footprint on the 2D B-spline 3 kernel function, approximated by a Gaussian kernel). Points outside have no influence on this location. A weighted linear regression is performed (order 1 in the implemented approach, order 2 for illustration only), the weighs being given by the kernel. The residuals from the local fit are used to compute the error estimate (standard deviation sigma). The quantity of interest is the probability distribution function (pdf) of the height.
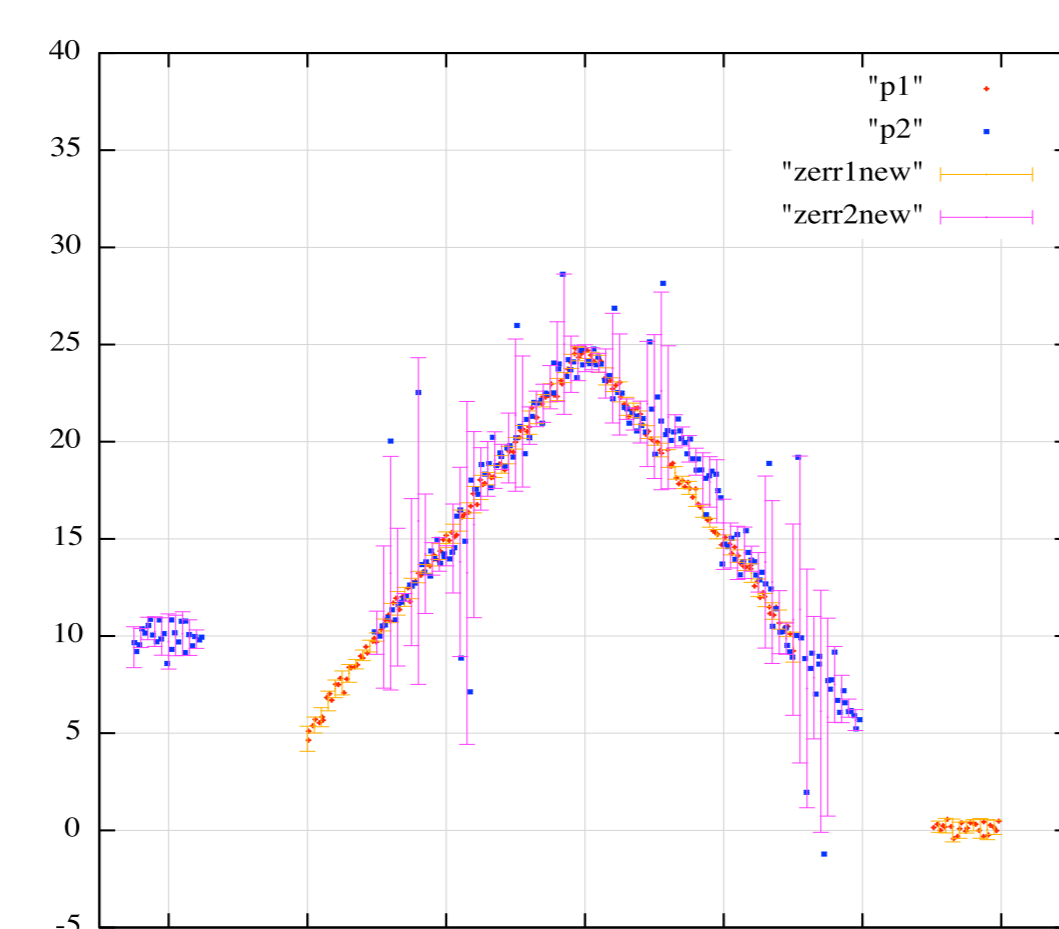

2D experiment with synthetic data, illustrating the probabilistic nature of the proposed method. Two point clouds (red and blue) are gridded onto a common grid with a local linear model, and the inferred pdfs are represented as error bars computed from the Student-t distributions of the height (orange and purple). Heights can be compared when estimates from both point clouds are available, and relevant changes are detected according to their significance.

Test: automatic registration
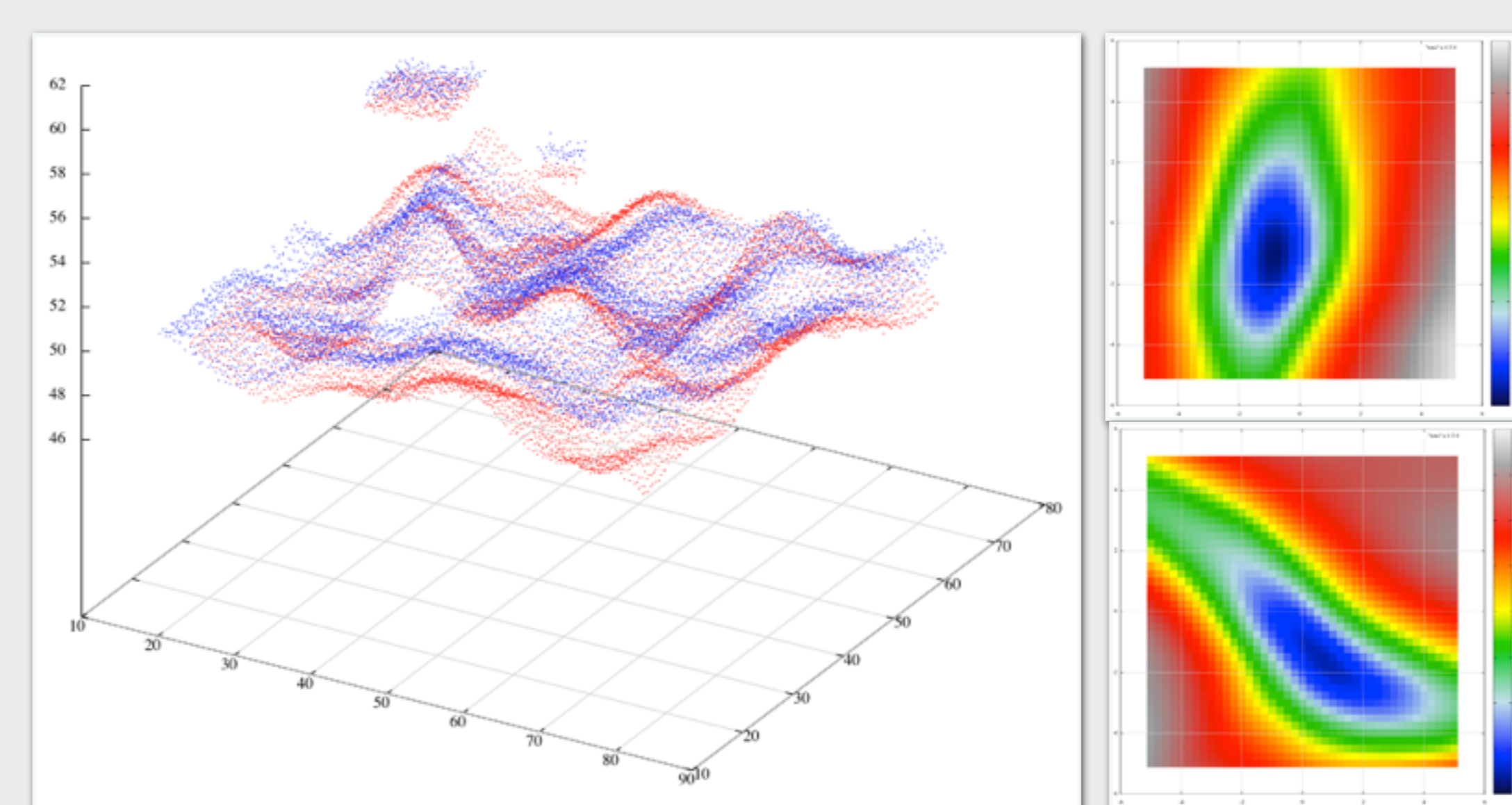
Automatic point cloud registration experiment: synthetic point cloud data.
Left: synthetic point cloud with smooth surface, building and changes.
Right: non-quadratic behavior of the energy function to be minimized for two different areas of interest.
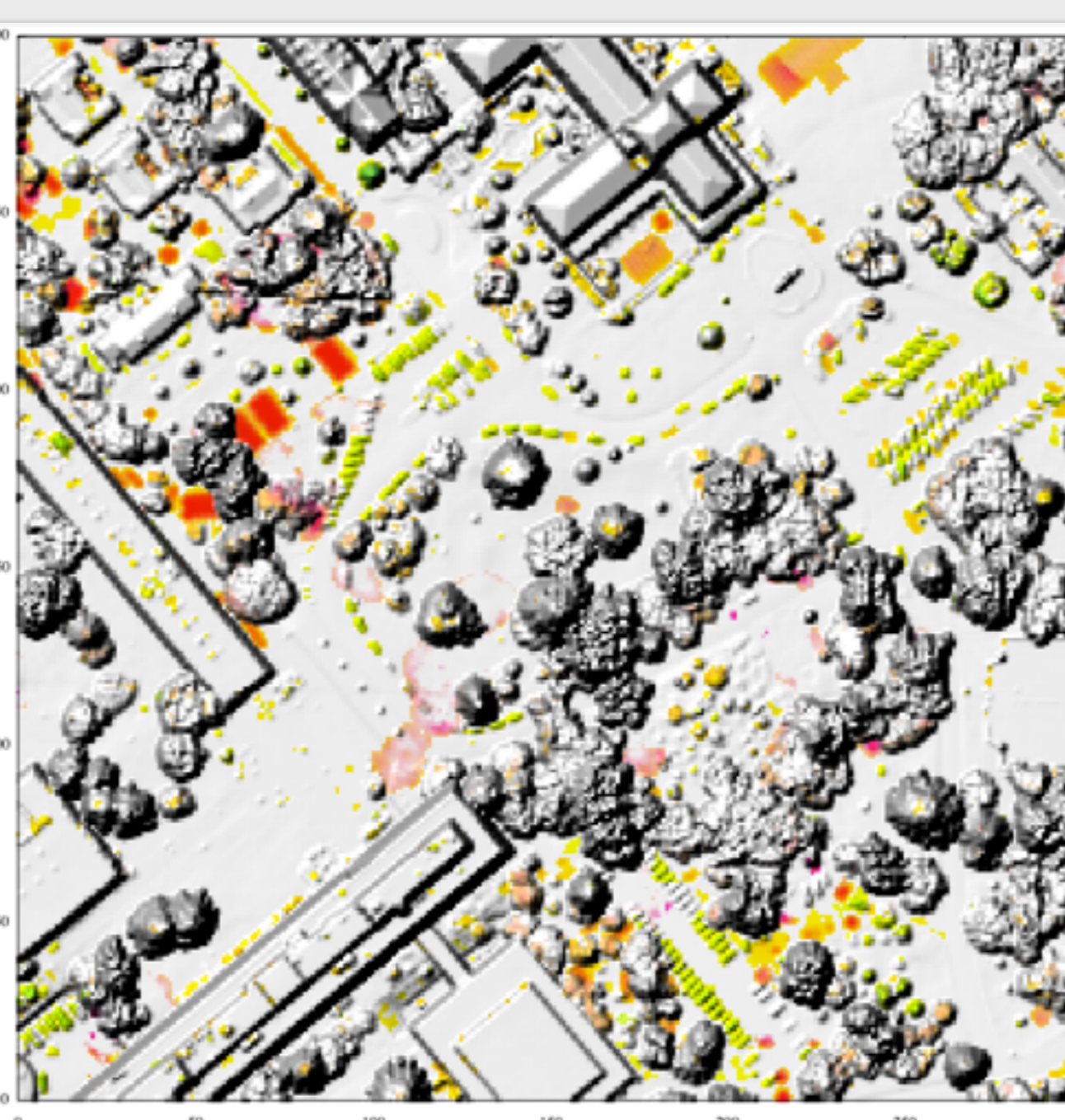
Validation: terrestrial scans
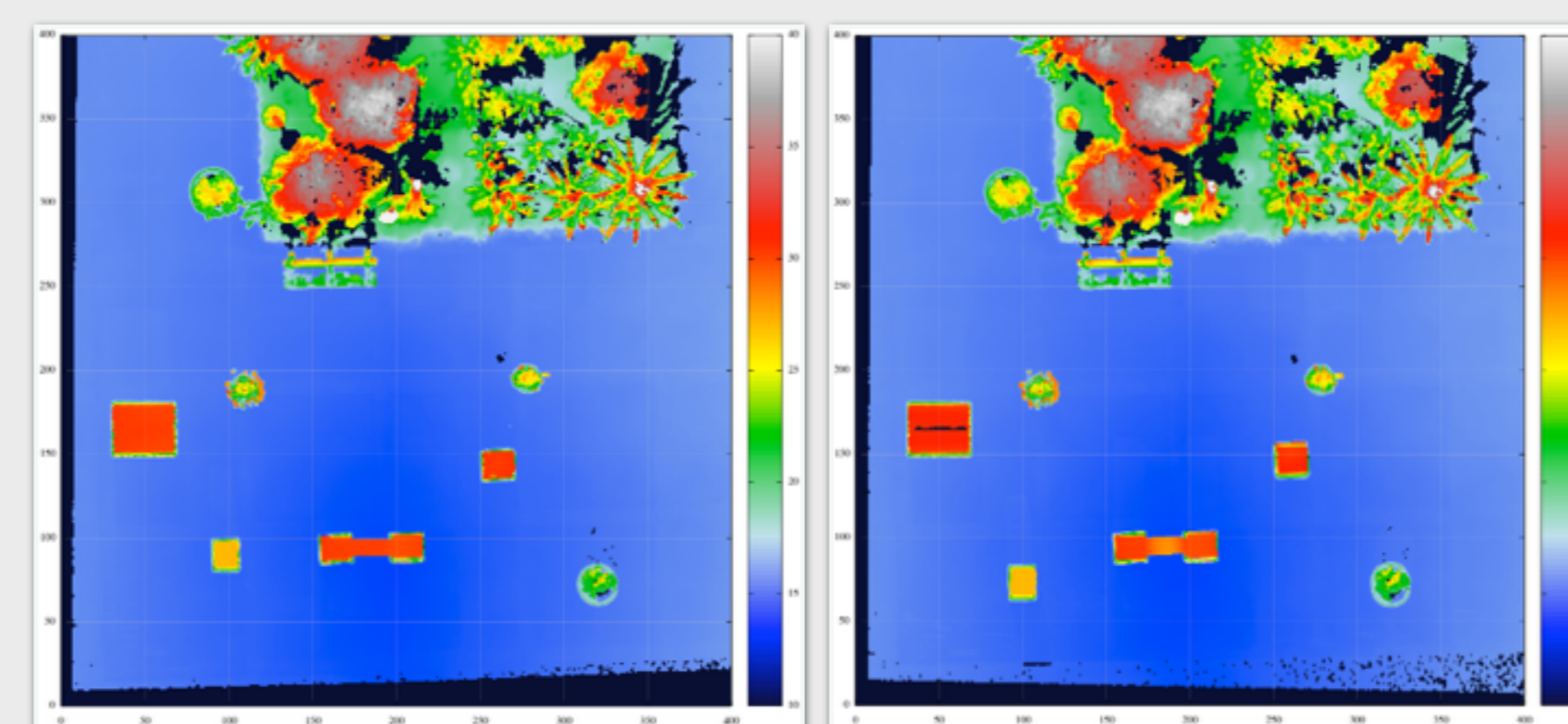
Big Box cardboard model, original density, at 0.5 m GSD. Experimental gap-based surface model filtering used. Left: baseline, right: changes applied (manually). Notice the deformed bridge, open box (left side) and shifted box (bottom left corner). The vegetated area is real and did not suffer any changes.
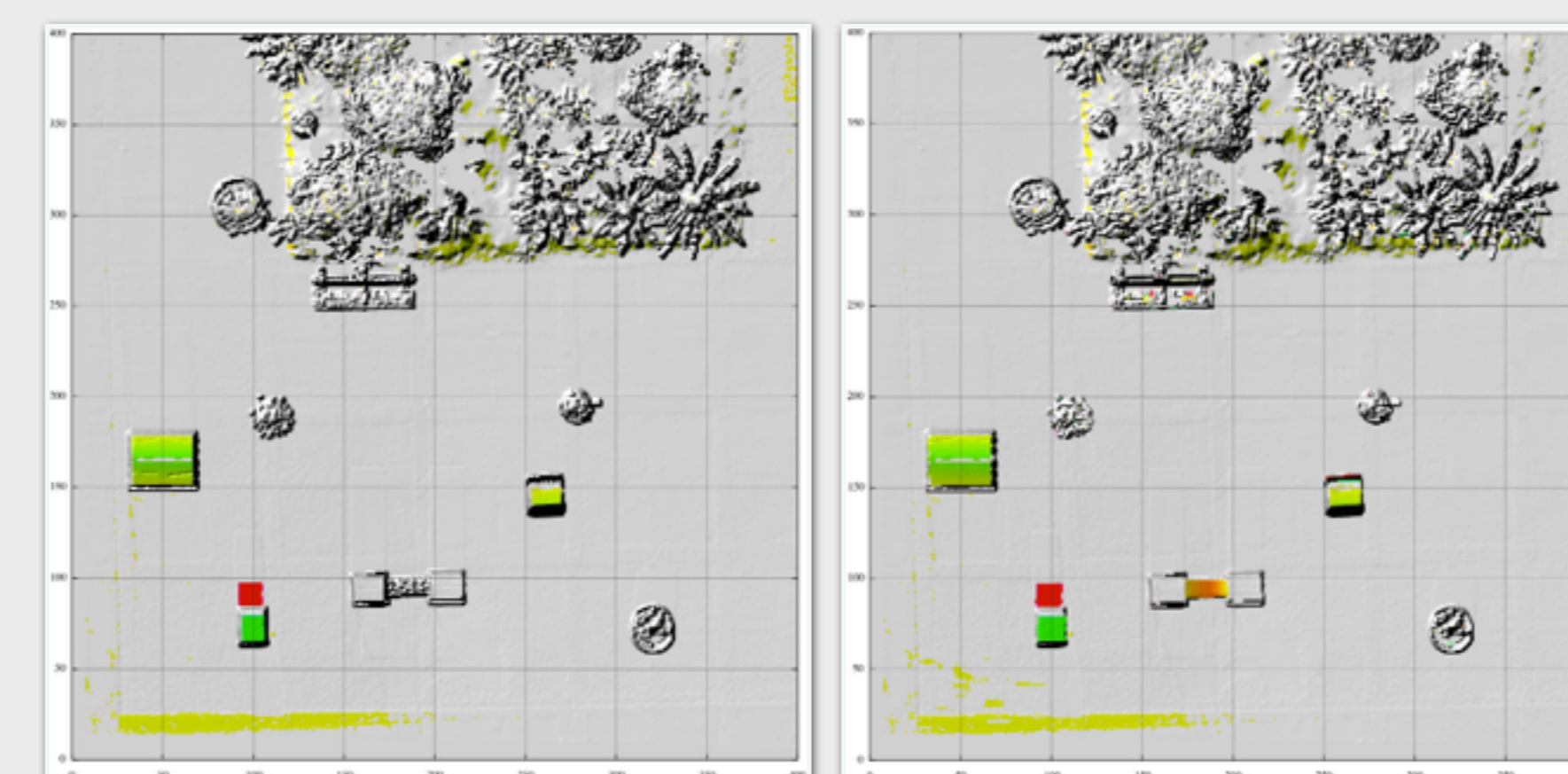
Big Box cardboard model, original density at 0.5 m GSD. Same color-coded shaded relief visualization as in the final results (below). Left: gap-based surface filtering not used. Right: filtering used, notice the deformed bridge in orange and less artifacts on the left box as only the top surface is selected. Some artifacts are due to the filtering method. Some of the detected changes are due to scan misalignment (each point cloud was collected by fusing two separate scans).

Proba. change map visualization

**Proposed color-coded shaded relief visualization and related color map.**

The shaded relief map helps locate the detected changes and uses the slope parameters from the highest resolution data. The hue represents the magnitude of the change (red for height loss, green for height gain in this example). The saturation decreases with increasing roughness, to help focus on flat (man-made) objects. The height differences are thresholded at 95% significance level (user-selected).

The red and orange areas correspond to real temporary buildings, and removed trees or branches.

Gridded change map product: WSI-NOAA, NPS campus, 300 m x 300 m area, 1 m GSD
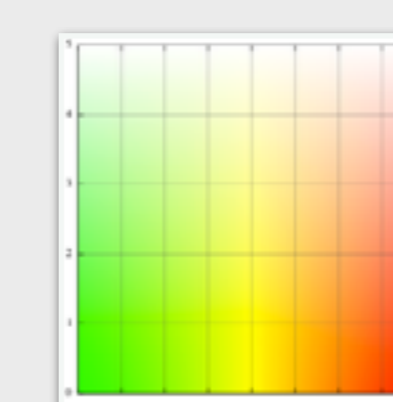
Gridding & significant differences
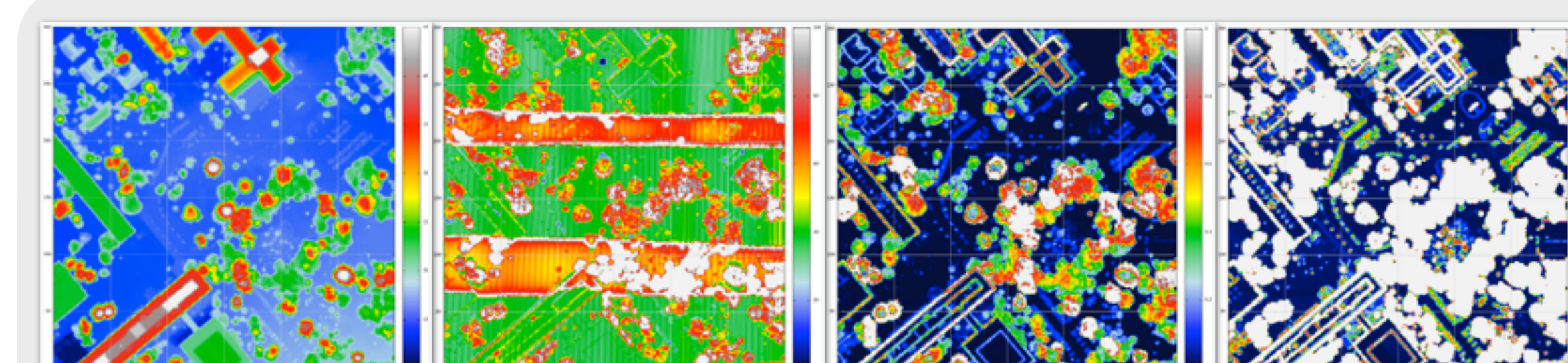
WSI tile 774, 1 m GSD.
Left: gridded height. Right: point density.
Left: 95% confidence interval corresponding to the Student-t marginal distribution of the height. Right: estimated noise standard deviation sigma. The uncertainty is much lower than 2 sigma due to the high point density.
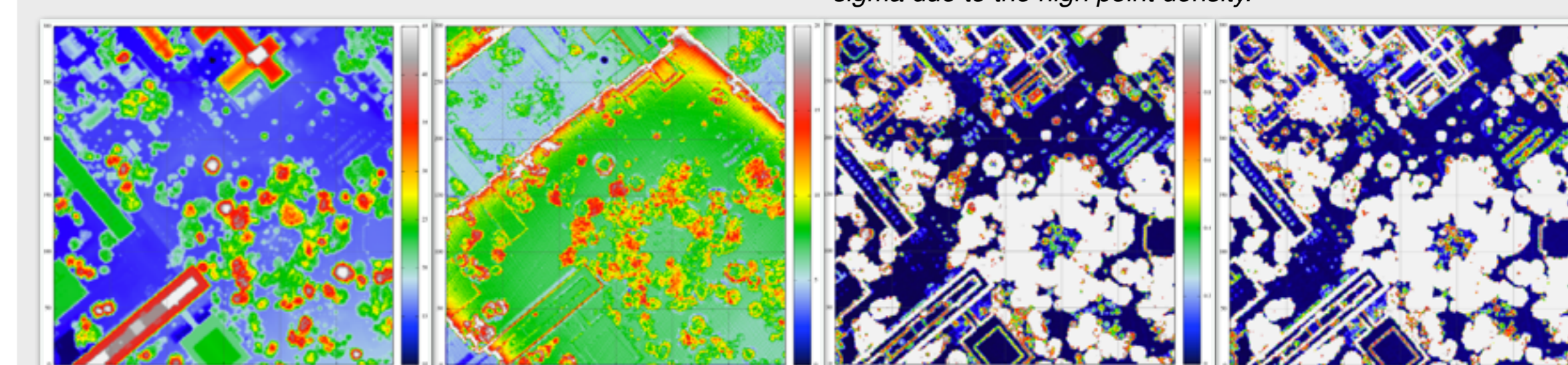
NOAA (cropped to WSI tile 774), 1 m GSD.
Left: gridded height. Right: point density.
Left: 95% confidence interval corresponding to the Student-t marginal distribution of the height. Right: estimated noise standard deviation sigma. The uncertainty is much lower than 2 sigma due to the high point density.
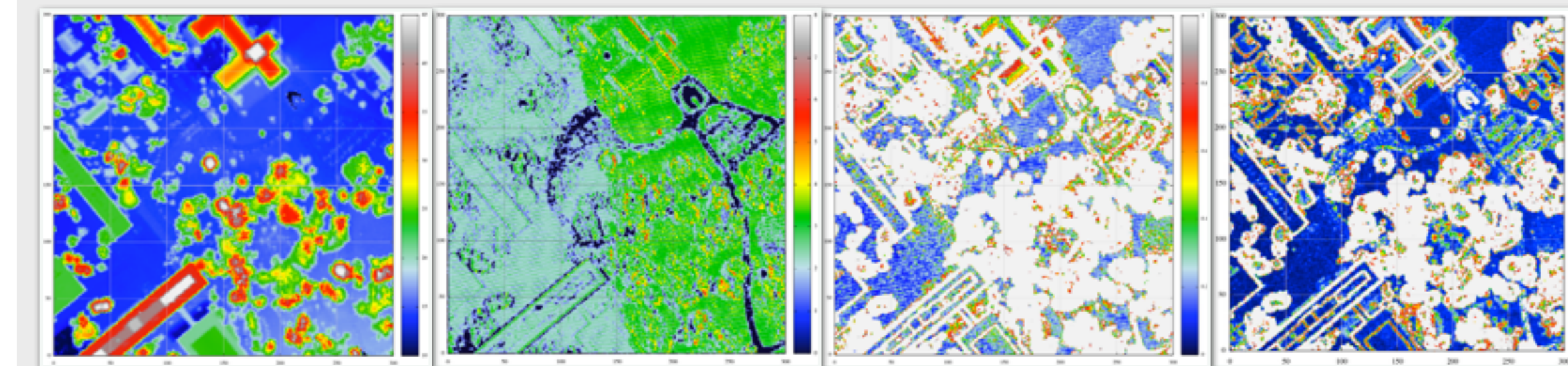
AMBAG (cropped to WSI tile 774), 1 m GSD.
Left: gridded height. Right: point density.
Left: 95% confidence interval corresponding to the Student-t marginal distribution of the height. Right: estimated noise standard deviation sigma. The uncertainty is higher than 2 sigma due to the low point density and the heavy-tailed behavior of the Student-t distribution.
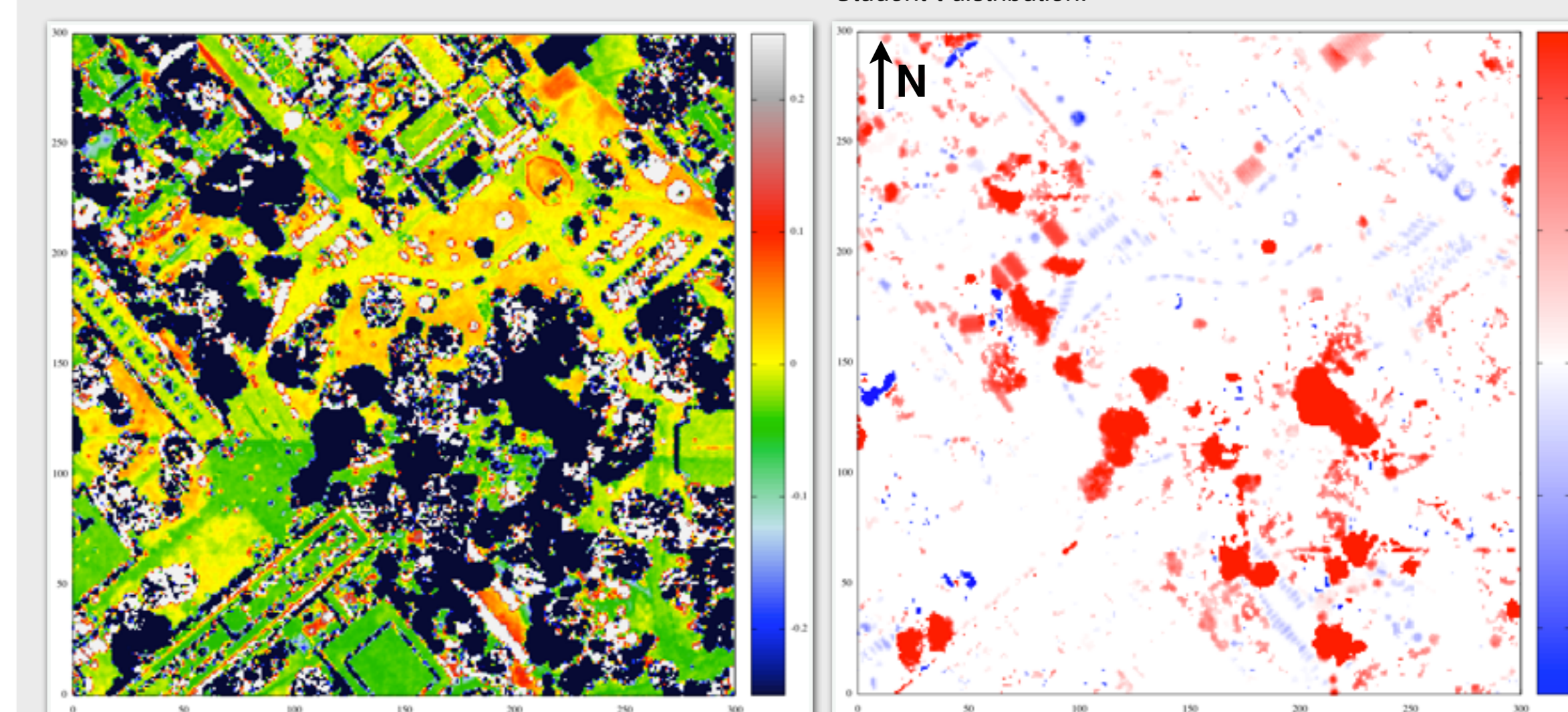
Gridded height difference: WSI-NOAA at 1 m GSD (AMBAG dataset not used).
Left: small changes, showing mostly geometric errors (aligned with swath coverage) and vegetation height variations. Right: large height changes, thresholded using 95% significance level. Remaining changes are real - tree cutting, landscaping, temporary buildings, vehicles etc.

Issues, Solutions, Future work

- ➡ Explicitly accounting for overlapping surfaces
- ➡ Full 3D non-parametric modeling
- ➡ Preliminary surface filtering to avoid overlaps
- ➡ Strip adjustment for IMU error reduction
- ➡ Use of predictive uncertainty and handling missing data

Conclusions & Recommendations

- ➡ **Point density**
  > 4 pts / grid cell (depends on target GSD)
- ➡ **Swath overlap**
  > 60% sidelap (>= 3 swaths in area of interest)
- ➡ **Sampling pattern**
  sampling distance should match footprint size (reduce aliasing)
- ➡ **Geometric quality**
  minimal inter-strip discrepancy, good IMU data
- ➡ **Raw discrete return data, if available**
  approx. predictive uncertainties (instead of empirical)
- ➡ **Raw waveform data, if available**
  rigorous predictive uncertainties (instead of empirical)